Working Paper

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Publication Date:
2016-10

Permanent Link:
https://doi.org/10.3929/ethz-a-010726288

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KOF Working Papers, No. 413, October 2016

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Innovation and Firm Growth over the Business Cycle

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October 2016

Abstract

This paper investigates how the macroeconomic business cycle impacts the empirical relation between firms' innovations and their sales growth rates. Based on firm-level panel data over the time period 1995-2014, the paper finds no visible sales growth differentials between firms in booming economic environments. In the economically difficult times of recessions, by contrast, innovative firms show significantly higher sales growth rates than non-innovative firms. This finding is in line with Schumpeter's (1939) business cycle theory, where recessions play an important role in the adaptation of the economy towards innovative products and processes. Moreover, the paper shows that small innovative firms, profiting from their higher organizational flexibility and stronger entrepreneurial commitment, are the main beneficiaries in this adaption process.

JEL-Classification: 033

Keywords: Innovation, Firm growth, Business cycle, Firm size

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1 Introduction

Schumpeter (1939) characterizes the business cycle as an absorption process the economy experiences through the introduction of new products and processes. Initially, innovations brought forward by firms move the economy away from its equilibrium position and cause it to expand. With increasing economic activity, market participants start to get overly enthusiastic and uncertainty spreads, leading the economy to peak and then, finally, to slide into recession. This latter drift into recession is thereby tantamount to an adaption of the economy to the beforehand introduced innovations. The empirical relation between firms' innovations and their sales growth rates is thus likely to vary over the business cycle as described by Schumpeter. The existing literature finds that innovative firms tend to have higher sales growth rates than non-innovative firms (e.g., Coad and Rao, 2008; Colombelli et al., 2013) and that this positive sales growth premium is contingent upon various factors such as the measure of innovation activities applied, the type of industry, the persistence of research activities, or the size of the firms (Demirel and Mazzucato, 2012). However, the existing literature does not link the innovation-growth relationship to the business cycle. In the paper at hand, we address this research gap in three steps.

First, we start out by testing the state of the art, that is, whether we can find additional evidence for our sample in line with an on average positive association between innovations of firms and their sales growth rates.

Second, we argue that the business cycle is a key determinant of this observed empirical relationship and that the growth premium innovators experience in times of economic recessions is larger than the one they experience in times of economic booms. Economic booms are characterized by a comparatively friendly environment, where most firms can achieve good performance, often irrespective of their actual competitiveness. Recessions, on the other hand, are associated with intensified competition between firms, which leads to substantial sales growth differentials between them. We argue that in such tougher economic environments, firms producing innovative goods with new technologies will be better able to maintain stable demand than firms producing outdated products with older technologies. We thus expect the positive relation between innovation and sales growth to mainly originate from economic recessions and less so from economic booms.

Third, given this hypothesized growth premium of innovators in recessions, we investigate which type of firm, the small or the large innovator, can profit more from such adverse economic situations. Since we characterize the adaption process towards the innovative the economy experiences in times of recessions as very discontinuous in nature, we argue that small innovators, thanks to their higher organizational flexibility and stronger entrepreneurial commitment, can gain additional room in recessions and thus outgrow the more inert, large innovative firms.

Using panel data of Swiss firms ranging from 1995 to 2014, the paper finds evidence confirming the outlined arguments. On average, when pooling all time periods, innovators experience significantly higher sales growth than non-innovators. However, when split by business cycle development, it becomes clear that this growth premium originates from the two recessions the Swiss economy experienced in the observed time span. Our results do not show any significant sales growth differentials between innovators and non-innovators in the less competitive times of economic upturns. Moreover, our estimations show that during the observed economic downturns, small innovators experienced significantly higher sales growth than large innovators, highlighting their ability to react to changing circumstances in due time.

The paper is organized as follows. Section two summarizes the relevant literature in order to derive testable hypotheses. Section three introduces data and shows how we construct the variables. Section four explains the empirical set up and the econometric models. Section five presents the estimation results of the described models. Section six shows various robustness checks supporting our main estimations. Section seven concludes and points at possible policy implications.

2 Literature and hypotheses

The following conceptual notions and hypotheses are motivated by Schumpeter's view that "the fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets, the new forms of industrial organization that capitalist enterprise creates" (Schumpeter, 1950, p.83) and his view that the business cycle results from this ongoing process of creative destruction (Schumpeter, 1939). Moreover, inspired by the ideas of the old Schumpeter (1950), the paper puts an additional emphasis on the role firm size plays in this process. Hence, the paper tries to empirically investigate Schumpeter's central notions about how innovation affects sales growth, how this innovation/growth relationship is shaped by the development of the business cycle, and whether this implies advantages for either small or large innovative firms.

2.1 The relation between innovation and sales growth

Theoretical literature suggests that innovation activities are of central importance for the sales growth of firms (see, e.g., Schumpeter, 1950; Romer, 1990; Geroski, 2005). Innovations in the form of novel ideas of entrepreneurs or researchers provide the economy with new products increasing consumer utility or with new production technologies improving firm productivity, whereby the two often go hand in hand in raising economic growth. However, the innovation process can also have desirable side-effects for firms.Geroski and Machin (1992) argue that innovating firms accumulate knowledge that might not be of immediate importance but instead increases the firm's capabilities to absorb external knowledge (Cohen and Levinthal, 1989) and opens up various novel technological trajectories (Del Monte and Papagni, 2003). The innovation process thus transforms a firm and makes it more perceptive and more flexible in the long-run. Of course, innovations do not always translate into economic growth; they can lead to a redistribution of economic rents only, as firms may increase their sales through innovations that are not connected to productivity but only steal market shares from competitors. However, also business stealing is reflected in a positive innovation-growth relationship. Consequently, economic theory teaches us that innovations are necessary for every firm that wants to outgrow its competitors in our constantly changing economic environment.

The empirical literature on whether innovation is positively related to firms' sales growth is less clear cut though. A well-founded example for a positive relation between innovation and sales growth is given by Colombelli et al. (2013), who find an unambiguous positive association between product, process, and organizational innovation and firm sales growth in various econometric specifications. Most other empirical studies, however, show that the innovation-growth relationship varies considerably with the characteristics of the underlying firms. Coad and Rao (2008), for instance, demonstrate that innovations have a large positive effect in the highest growth percentiles but, at the same time, also a slightly negative effect in the lowest growth percentiles. The authors explain this result by the high degree of chance involved in the success of products emerging from R&D activities. Some firms simply bet on the "wrong horse", which becomes clear only with hindsight. Demirel and Mazzucato (2012) investigate a sample of pharmaceutical firms in the US. They show that the R&D stock (normalized with sales) is positively related to sales growth only for smaller and persistently (over 5 years) patenting firms. For firms with more than 500 employees, the R&D stock has a significantly negative sign. Del Monte and Papagni (2003) emphasize the different effect R&D intensity has in high-tech sectors as compared to low-tech sectors. In high-tech sectors, the required high R&D intensities serve as a veritable barrier to entry that guarantees firms high returns to R&D. In the less R&D intensive low-tech sectors, by contrast, entry is more feasible and innovations are thus easier copied, which implies that the returns to R&D are lower in those sectors.

Hence, it becomes already clear from these three studies that the innovation-growth relationship depends on various characteristics such as the sector under investigation, the size of the firm, the persistence of the innovation activities, the measure of R&D applied, or whether we look at the winners or losers of the innovation process. It is thus not surprising that there are also empirical studies that show an insignificant relationship or even a negative relationship for firms with certain characteristics (Rosenbusch et al., 2011). Demirel and Mazzucato (2012) conclude from the general ambiguity of results that there is obviously still much to learn about the details of the innovation-growth relationship. But given the clear theoretical propositions and the on average positive innovation-growth relationship in the empirical literature, we formulate the first hypothesis as follows:

Hypothesis 1 *Innovators experience higher sales growth rates than non-innovators*

2.2 The relation between innovation and sales growth over the business cycle

Schumpeter (1939) characterizes business cycles as an inherent part of capitalism; they result from the unstable, oscillating growth path on which creative destruction develops. Whereas in the paper at hand we do not consider whether innovations are indeed the cause behind the cyclical upswings of the business cycle, our emphasis lies on the final stage of the business cycle as described by Schumpeter, the recession, which he depicts as a process of adaption and readjustment towards innovative goods and production technologies. In economic booms, most products sell well, which makes it easier to prosper for all firms in the economy alike. Recessions, by contrast, introduce a harsh competitive environment that creates large performance differentials between firms (Bloom, 2014). We argue that those firms that have timely introduced a new consumer's good, a new production technology, or a new form of organization will be better prepared to face this harsh environment. Firms offering outdated goods produced by an old technology, on the other hand, will be likely to lose ground in the market and experience more negative growth. Thus, in line with Schumpeter's business cycle theory, we argue that the positive sales growth premium innovators enjoy is mainly rooted in the downturns of the macroeconomic business cycle, where the economy reorganizes and, more importantly, renews itself.

Schumpeter's business cycle theory is often interpreted as being valid for long-run fluctuations only. Contrary to this popular reception, Schumpeter (1939) himself (rather arbitrarily) differentiates between three types of economic fluctuations with different time spans: Kondratieffs (60 years), Juglars (9 years), and Kitchins (3 years), where each Kondratieff contains an integral number of Juglars and each Juglar an integral number of Kitchins. In the paper hand hand, we focus on the macroeconomic business cycle as defined by positive growth followed by negative growth. Schumpeter himself argued that the macroeconomic business cycle need not necessarily coincide with his understanding of the business cycle, with the three fluctuations working their way simultaneously. Nonetheless, we will test whether his theory also extends to the macroeconomic business cycle, the cycle that is of actual interest to both economists and the public. The paragraphs that follow describe the mechanisms working in recessions in more detail, for both product and process innovations.

In economic downturns, the intensified competition between firms, induced by the collapse in aggregate demand, usually leads to a decrease in prices. Those firms that dispose of an innovative, more efficient production technology are, thanks to their higher margins, better able to keep up with lowering prices and other means of intensified competition, such as improved advertising, customization, or service; all necessary steps to offer security to anxious consumers. Firms with an older, less efficient production technology, on the other hand, have troubles to compete and due to their inflexibility to take action experience more negative growth and, consequently, lose market shares. The relative shift of aggregate production towards the innovative, more efficient firms leads to an on average higher productivity in the economy. In the literature, this productivity enhancing effect of recessions is put forward under the name of the "cleansing effect of recessions" (Caballero and Hammour, 1994) or the "virtues of bad times" (Aghion and Saint-Paul, 1998).

To complete the picture, it is also relevant to know which products will be affected most by the shrinking aggregate demand in recessions. The events happening in economic booms thereby represent the key to understand the shifts in purchasing decisions of market participants. The good performance of firms in economic booms is to a large degree the result of an overly enthusiastic market environment with partly suspended market mechanisms. Consumers and firms do not base their decisions on fundamentals anymore, which results in substantial misallocations of resources. Many firms achieving considerable success would not merit such a good performance under normal circumstances. Market participants start to notice their mistakes usually only after the overheated economic activity has come to an end and the economy starts to slide into a recession.

Short in liquidity, both consumers and firms then update their non-optimal purchasing decisions and become more selective; they opt for less but better deals. This increases competition in the product market and singles out those products that prove to be best. Innovative products are likely to emerge as winners from this process. This may be because they are cheaper, more technically advanced, of a higher quality, more user-friendly, or simply more fashionable. On the other end of the product spectrum, by contrast, the external pressure induced by the recession leads consumers to sort out outdated products of lower value. Clearly, the higher selectivity of consumers in recessions is likely to manifest itself to a substantial degree in a higher price-sensitivity, though this mainly holds for products that consume a high share of wallet (Gordon et al. 2013). An increased responsiveness to prices favors those innovative products that offer a lower price because they, for example, require less resources or are greatly simplified. That innovation often means lower prices is not a very well recognized fact, though it is for instance very visible in the personal computer industry, where innovations usually are expressed in faster models at lower prices.

However, since cash-strapped consumers want to get more utility out of every currency unit they spend, it is the higher consumer surplus of innovative products that makes them more attractive to consumers. Of course, radically new innovations will only stand a chance with consumers when the benefits they offer are large enough, as they often carry a high degree of uncertainty with them. A prominent example in this respect is the first iPhone, introduced by Apple at the edge of the Great Recession, which was an incredible success despite its high price and the declining aggregate consumer demand that followed. Nonetheless, on average, product innovations always offer a higher consumer surplus than existing products, which is the reason why they prevail in the economy and replace older products. But in line with Schumpeter, we argue that the recession is the moment where this replacement happens; outdated products get eliminated from the more careful purchasing decisions of market participants and the whole economy adapts to those innovative products that prove to be best. Consequently, we argue that those firms providing innovative and up-to-date products at the moment the recession strikes are better able to hold their demand stable than non-innovative firms.

Recessions are, however, not a smooth process allowing the economy to only gradually and slowly adjust to innovative goods and production technologies. Business cycles are highly asymmetric, with recessions shorter but much sharper than booms (Caballero and Hammour, 1994). Under the intensified market conditions in a recession, the development of demand towards those innovative products that prove to be best may take quite unanticipated directions. It is often impossible to know in advance which products will sell well in the market. In order to not lose ground, many firms will thus have to undergo a painful process of modernization and rationalization. This holds as well for some of the innovators; for example those that set on the wrong products or technologies and now, because of the increased competition, suffer from a collapse in demand (Coad and Rao, 2008). In this respect, Geroski and Machin (1992) emphasize the positive side-effect running an R&D department can have, as R&D activities give firms the capability to better adapt to changing environments. By running an R&D department, firms dispose of the knowledge necessary to pursue various different technological possibilities. This knowledge provides them with the ability to quickly adapt to movements by competitors or the market as a whole. Thus, in economically difficult times, R&D firms can spur their production faster in the direction of the most desired products that guarantee them stable demand.

Hence, we argue that innovative firms running R&D activities can better resist recessions because, first, they dispose of up-to-date goods and production technologies and, second, they have the necessary flexibility to adequately react to changing market environments. Both arguments are consistent with the notion that it is the "hard times" that show a firm's actual competitiveness. We therefore expect that innovators experience a higher sales growth premium over non-innovators in times of economic recessions:

Hypothesis 2 *The sales growth premium of innovators is larger in recessions than in booms*

Note that in Switzerland the financial crisis of 2008 was felt less strongly than for example in the US. Hypothesis H2 will only hold for moderate economic recessions and not for severe depressions, such as, for instance, the Great Depression of the 1930s, where economic pressure is so strong that market selection gets quite arbitrary and many profitable but illiquid firms go bankrupt.

2.3 Small innovators as the main beneficiaries in recessions

An important part of Schumpeter's contribution to economic theory is concerned with the advantages and disadvantages of large firm size in the R&D process. Whereas large firms have decisive advantages in terms of scale economies, financial resources, and market dominance (Schumpeter, 1950; Cohen, 2010), the strengths of small firms mainly lie within their behavioral characteristics. "Smallness" is generally aligned with little bureaucracy, rapid decision-making, proximity to customers, and the capability of fast learning (Vossen, 1998; Nooteboom, 1994; Rothwell, 1989). We argue that in the discontinuous times of recessions, these characteristics give small innovative firms a decisive advantage over large innovative firms, since flexibility and adaptability are key requirements for timely launching of new products corresponding to the changing consumer needs (towards the emerging "winning products"). Small innovators will also be quicker in making their production structure and firm organization more efficient, following the newest production technologies, and get rid of any slack; steps that, contrary to orthodox economic theory, are often only taken when times are getting tougher. Large innovators, by contrast, will have more problems to take advantage of such periods of discontinuity, as they suffer from organizational inertia due to their large bureaucracy, many hierarchy levels, and organizational routines that all hamper change (Hannan and Freeman, 1984, e.g.,).

In addition to these organizational advantages, we argue that in times of recessions small innovative firms enjoy a further central advantage over large innovative firms: the strong commitment on behalf of the respective entrepreneur or owner (Wiggins, 1995; Vossen, 1998). In adverse times, the will to defend the firm at all costs is much larger in small firms than it is in large firms. In small firms, the owner usually personally identifies with the firm and will do anything in his power to avoid bankruptcy. In large firms, by contrast, the salaried executives often bear more of an employee attitude and have less personal affiliations to the company they work for. Or to quote (Schumpeter, 1950, p.141f) on the transition from small enterprises to large concerns: "substituting a mere parcel of shares for the walls of and the machines in a factory, takes the life out of the idea of property. It loosens the grip [...] in the sense that the holder of the title loses the will to fight, economically, physically, politically, for 'his' factory and his control over it, to die if necessary on its steps".

There remains the question why the outlined small size benefits should not also work in favor of small non-innovative firms and give them a lead over large firms in general. In line with Davidsson (1989), we argue that it is the entrepreneurial spirit itself that differentiates small-innovative firms from small non-innovative firms. In the population of small firms, non-innovative firms clearly outnumber innovative firms (also in the representative sample of the Swiss economy we use). But these non-innovative firms, in contrast to the innovative ones, usually also remain small and do not grow larger over time. Of course, setting up a new firm is per definition always an entrepreneurial act. However, it is only one step; for a successful growth development the firm needs continued entrepreneurship on behalf of the owner, with a vision to actively pursue change in the economy. Given that circumstances are right (ability, market niche, timing, etc.), this entrepreneurial spirit is largely discretionary and most small firm owners deliberately chose not take the daring and risky activity of continued entrepreneurship; they are not guided by the desire to grow larger but rather to live an autonomous, self-determined, and traditional way of life (Nooteboom, 1994). They provide craftsmanship based on continuity and differentiation to their customers, as in the case of, for example, the owner of a specialized restaurant, who finds fulfilment in providing high quality food to his customer-friends. Thus, when comparing small innovative and small non-innovative firms, we speak of a very different sample of firms. Whereas the former will take any opportunity to revolutionize economic life, the latter are satisfied with maintaining their current business and do not strive for additional growth, even when circumstances are changing, like it is the case in recessions. We therefore formulate the last hypothesis as follows:

Hypothesis 3 *In recessions, small innovators achieve higher sales growth rates than large innovators*

3 Data and definition of variables

In order to test the derived hypotheses, we make use of seven waves of the Swiss Innovation Survey (SIS), covering the period 1995-2014. The surveys are based on a stratified random sample drawn from the Swiss business census for firms with more than five employees, including all relevant industries in the manufacturing, construction, and service sector. Stratification is on 33 industries and within each industry on 3 firm size classes. The SIS parallels the well-known Community Innovation Survey of the European Union.

The response rates for the different survey waves vary between 32% and 40%. For every wave, telephone interviews on a sample of 500 non-responding firms were conducted to assess a potential non-response bias. Analysis on the most important variables like yes/no to innovation activities showed that the data does not contain systematic bias inflicted by the non-response of firms to the written questionnaire. Since the surveys are very comprehensive and include different types of questions, a common response bias by answering strategically is very unlikely. Moreover, the survey uses several procedures that correct or reduce a common response bias. The complexity of the questionnaire requires that, especially within large firms, more than one person provides the data and information; for instance, R&D related information stems from the R&D department, while questions related to the overall firm performance stem from the accounting department. In sum, we can make use of an unbalanced panel of 7279 observations (3266 firms).

The sales growth rate (dependent variable) is in line with the literature defined as the difference in logarithmic sizes, where $sales_{i,t}$ stands for the logarithm of sales of firm "i" in time "t". This definition has the advantage of being additive and symmetric:

$$sales\_growth_{i,t} = sales_{i,t} - sales_{i,t-1}$$

Table 1 summarizes the sales growth rate developments for the seven covered time spans. It shows an on average positive sales growth rate for 1995-1998, 1998-2001, and 2004-2007. In contrast, an on average negative sales growth rate is observed for 2001-2004 and 2007-2010. These numbers quite accurately reflect the development of the Swiss business cycle over the observed period as published by the official statistics (for Economic Affairs SECO, 2014). In the two periods 2010-2012 and 2012-2014, the sales growth rate is positive but very small. In order to find out how long the recession of 2008 actually lasted, we draw on Swiss firms' own assessments (Arvanitis et al., 2014). It turns out that for over 60% of the firms in the Swiss economy the recession lasted well into the year 2011. We will therefore regard the period 2010-2012, despite its slightly positive growth rate, as part of the financial crisis of 2008. The period 2012-2014, by contrast, we regard as an economically stable period, as after 5 years of recession market selection should be over and firms should have already adapted to innovative products and production technologies. During the whole time span 1995-2014, we therefore observe four economic upturns or economically stable periods (1995-1998, 1998-2001, 2004-2007, and 2012-2014) and three economic downturns (2001-2004, 2007-2010, and 2010-2012).

The innovation variable is coded as 1 if there is a product or process innovation in the current time span and there has been R&D activity in the lagged time span. For example, the variable equals 1 if the firm introduced an innovation in 2007-2010 and the firm had also been running R&D activities in 2004-2007. As outlined in the theoretical background, the introduction of an innovation signals that the respective firm has up to date production lines produced by an efficient technology. The presence of R&D activities in the lagged time span, on the other hand, signals a comprehensive knowledge stock, increasing the firm's ability to adapt to changing environments. Because of this coding we will hereof refer to our central explanatory variable as R&D innovation.

The regression equations that follow in the empirical implementation include a number of control variables. Table 2 gives a short summary of those variables. Most important, we include two variables to control for the firm's contemporaneous liquidity situation. In recessions, for R&D firms to be able to successfully reorganize themselves, they need enough cash to finance these operations. For example, Aghion et al. (2012) show that in the absence of credit constraints, R&D investments as part of total investments move counter-cyclically, whereas in the presence of credit constraints they move pro-cyclically. Since small firms are generally more credit constrained than large firms, we may in recessions underestimate the growth of small R&D innovators as compared to large R&D innovators, because the former may not have the necessary means to successfully realign their innovation activities. We therefore introduce two variables from the SIS that measure for every firm individually the equity and credit constraints they face in their innovation activities. Both variables range on a subjective scale from "1" not relevant to "4" very relevant.

As a further important control variable, we include the firms' export shares. Switzerland's economy is characterized by a great number of exporting firms. The share of exporting firms in the Swiss economy is 29%, whereby among innovators the share is 62%.[1] Since the 2008 financial crisis was for Switzerland mainly an imported recession that only then spread to the rest of the economy, innovators were especially prone to suffer from this recession. Hypothesis H2 is therefore likely to underestimate the actual performance premium accruing to innovators, unless we add the export share of each firm as a further control variable. This is also important in respect to H3, because larger innovators are more integrated within international markets. Therefore, if we are not controlling for the export share, it is likely that we find a potential performance premium

[1] These numbers are calculated from the SIS by controlling for stratification.

for small innovators that actually results from the fact that these small firms are better protected from international shocks, as they can profit from the more stable domestic market and, due to the revaluation of the Swiss currency, lower import price. Including the firms' export share, ranging from 1 to 100, allows us to partial out this confounding effect.

The variable price competition controls for the possibility that the innovation growth premium is mainly the result of innovative firms operating in market niches where competition is only limited, a phenomenon often observed in the Swiss economy. This variable is categorical and measured on a subjective scale ranging from "very weak competition" (1) to "very strong competition" (5). Last, we include a variable controlling for share of employees having a tertiary education, which ranges from 1 to 100. It serves as an indicator of firms' human capital and is included to measure the effect of innovations more exactly, that is, that its growth effect is not actually driven by the better qualification of employees in, for example, large innovative firms. All regressions additionally contain a set of industry and region dummies. Industry dummies are created on 2-digit level for 33 different industries. Region dummies are based on the 7 Swiss greater regions, such as Zurich or Ticino.

Table 2 also shows the descriptive statistics for all the variables in our empirical model. The statistics are restricted to the number of observations actually used in the regression, that is, to the number of observations that remain after merging the seven waves of the SIS. Moreover, in all descriptive statistics and regressions extreme growth observations (more than +300%) were dropped, since OLS is extremely sensitive to such outliers. To make the distribution of the logarithmic dependent variable symmetric again, we also dropped negative growth rates with a value larger than -75%. This amounts to a drop of 1.4% of all observations. Standard errors improve massively without these outliers. This indicates that for extreme growth observations our hypotheses do not really hold. The threshold is arguably set quite randomly, but results do not at all prove sensitive to a further drop of outliers. Consider that the super growth of individual firms is anyway hardly measurable within a regression context measuring average changes, as such firms seldom follow regular patterns. Case studies would probably be more helpful in understanding those often highly influential super growth firms.

4 Empirical strategy

In this section we introduce the reader to the econometric models that allow testing our proposed hypotheses H1-H3. In order to test H1, we formulate Equation (1). This model you can find in, for instance, Colombelli et al. (2013). In order to replicate their results, Equation (1) will be run on the full panel by pooled OLS, random effects, between effects, and fixed effects. $\sum_{k=1}^{5} \beta_k X_{k,i,t-1}$ thereby represents the set of control variables described in the data section; export share, qualification of employees, competitive environment, and equity and credit constraints. The main interest will be on whether there is a growth premium associated with the introduction of a product or process innovation from a formerly R&D active firm, as indicated by β_2.

$$sales_{i,t} - sales_{i,t-1} = \beta_0 + \beta_1 sales_{i,t-1} + \beta_2 rndinno_{i,t} + \sum_{k=1}^{5} \beta_k X_{k,i,t} + \epsilon_{i,t} \tag{1}$$

As can be readily observed, Equation (1) actually contains the lagged dependent variable, which raises concerns for estimation, because in short panels like ours OLS results for β_1 would suffer from an upwards bias (Roodman, 2006). Imagine a large positive shock in period "t-1" that is not modelled by the variables in Equation (1). This shock will go into the composite error term and $sales_{i,t-1}$ will be higher. But this shock will also (at least partially) be incorporated in the firm fixed effect, which means that $sales_{i,t}$ will be higher too. Therefore, in period "t" you will get a positive correlation between the lagged dependent variable $sales_{i,t-1}$ and the dependent variable $sales_{i,t}$ that is actually due to a correlation of $sales_{i,t}$ with the firm fixed effect. The most obvious solution in this case would be a fixed effects transformation. But a simple fixed effects transformation like demeaning or including firm dummies will lead, in contrast to the untransformed OLS, to a downward bias of β_1 (Nickell, 1981).

However, there is an important special case where simple OLS estimates are not biased, namely when the variable $sales_{i,t}$ contains a unit root (Bond et al., 2002). Given the broad literature on Gibrat's law, it is a likely instance that firm growth actually has a unit root and follows a non-stationary growth process (Geroski, 2005). It is important for us to know whether conditions are such that OLS estimates are not biased, because in the paper at hand we run regressions for every cross-section separately and we therefore cannot make use of panel data methods. Since we have an unbalanced panel data set, we cannot use popular tests for unit roots in panels like Harris-Tzavalis or Im-Pesaran-Shin (Bond et al., 2002), because their implementation requires strongly balanced panel data. However, we can resort to system GMM (GMM-SYS) as developed by Blundell and Bond (1998) and apply it to our central explanatory variable $sales_{i,t}$. In contrast to traditional difference GMM, GMM-SYS has the advantage that it is also identified in the case of a unit root and, consequently, provides a valid test in our respect (Bond et al., 2002). This means that if the coefficients in the GMM-SYS estimation indicate the presence of a unit root, we will be able to have some confidence in applying simple OLS.

In order to test H2, we run Equation (1) on every cross-section separately. These separate cross-sectional regressions allow identification of how R&D innovators differ in their sales growth from non-innovators over the business cycle.[2] According to hypothesis H2, β_2 of Equation (1) should be larger during cyclical downswings than during cyclical upswings.

In order to test hypothesis H3, whether in times of recessions small R&D innovators achieve a performance premium over large innovators, we formulate Equation (2). It differs from Equation (1) by the inclusion of an interaction term between $rndinno_{i,t}$ and $sales_{i,t}$. This provides a compact way to compare all four groups of firms that are relevant to our three hypotheses: i) small R&D innovators, ii) large R&D innovators, iii) small non-innovators, and iv) large non-innovators.

$$\begin{aligned} sales_{i,t} - sales_{i,t-1} = \beta_0 + \beta_1 sales_{i,t-1} + \beta_2 rndinno_{i,t} + \\ \beta_2 rndinno_{i,t} * sales_{i,t-1} + \sum_{k=1}^{5} \beta_k X_{k,i,t} + \epsilon_{i,t} \end{aligned} \tag{2}$$

In models with interaction terms, the interpretation of the two variables that are part of the interaction term changes drastically compared to their interpretation in simple additive models (see Brambor et al. (2006) for an illustrative description of models with interaction terms). In Equation (1), β_2 shows whether R&D innovators experience a sales growth premium over non-innovators, holding all other covariates at their mean. In Equation (2), by contrast, β_2 shows whether R&D innovators experience a sales growth over non-innovators, holding $sales_{i,t-1}$ at the value of zero and, similarly, all other covariates at their mean. Since we have rescaled the variable $sales_{i,t-1}$ by subtraction of its smallest value, the coefficient β_2 shows the sales growth premium small R&D innovators experience over small non-innovators; that is, it compares the two groups i) and iii). The coefficient β_1, on the other hand, shows the sales growth differential between small non-innovators and large non-innovators (holding the R&D innovation variable at the value of zero); that is, it compares iii) and iv). We did not formulate a hypothesis for this relationship. Finally, the joint significance of β_1 and β_3 shows whether large R&D innovators differ from small R&D innovators, that is, it compares i) and ii). In accordance with H3, we expect the joint significance between β_1 and β_3 to be significantly negative in times of economic crisis; small R&D innovators should outgrow large R&D innovators.

There might be the objection that we do not lag our central explanatory variable $rndinno_{i,t}$. We model the introduction of a new product or process in, for example, the period 2010-2012 (emerging from R&D in the lagged period) and measure its correlation

[2]See Archibugi et al. (2013) for a similar procedure to identify business cycle effects.

with the sales growth rate in the same period 2010-2012. Of course, product innovations usually take some time before they translate into commercial success. However, with our specification we want to identify those firms that have new products available at the time the crisis strikes. We predict that those firms that have the newest products and the newest production technologies available at the exact time the competitive pressure is strongest will be best able to master an economic crisis.

In a last step, we apply a different dependent variable to test for the consistency of our hypotheses. This variable is an ordinal variable measuring the general situation of a firm after the crisis, based on three mutually exclusive categories: "weaker", "the same" and "stronger". This (subjective) firm assessment was collected in the course of the innovation survey 2013. Since it is an ordinal variable, we will estimate its relation to our explanatory variables by ordered logit.

5 Results

Table 3 presents the results of our baseline model. We find a significantly positive relation between R&D innovations and sales growth in the OLS, RE, and BE, but not in the FE specification. Hence, the positive sales growth premium for R&D innovators results mainly from the cross-sectional dimension. The R&D innovation variable is not statistically significant over the time dimension, as can be seen in the FE specification. This is not a surprising result, because R&D activity, which is part of our variable, is a structural characteristic that has only little variation over time. When looking at the innovation yes/no variable only, that is, without connecting it to R&D activities in the lagged period, the FE estimation becomes significantly positive as well. However, our hypothesis relate to innovations stemming from R&D, signalling a broad knowledge stock, and not to the more sporadic and less radical nature of innovations not based on R&D. We explicitly want to compare those firms bringing forward innovations based on R&D with those firms that either do not run R&D or do not put forward innovations. We therefore have to rely on cross-sectional variation only. Clearly, R&D active firms may differ from non-innovative firms in other characteristics too, which is why we introduced our set of control variables as well as industry dummies and region dummies. [3]

Table 5 and Table 6 present the most important results in order to test our hypotheses H1-H3. Simple OLS is applied in the separate cross-sectional regressions. We apply OLS

[3]Note that the sales variable indicates a non-stationary process. This means that in Table 3 we are measuring a growth model. A significantly negative coefficient of the size variable, by contrast, would imply that we are actually looking at a stationary development of firm size and significant explanatory variables would only measure deviations from equilibrium firm size rather than long-term growth rate differentials.

because the results in Table 4 for the whole panel indicate the presence of a unit root. The coefficients of the lagged dependent variable in both the OLS and the GMM-SYS estimation are very similar and both larger than unity. The presence of a unit root in our sample implies that firms do not converge to an industry wide optimal output level around which there is noise in, say, the form of an AR(1) process. Rather, in combination with the fact that some of the industry dummies are significantly different from zero, it indicates the presence of various non-stationary processes with respective industry specific drifts. If there was any convergence towards a common equilibrium size on some sub-industry level, the GMM-SYS estimate would show a coefficient below unity. The consequence of the presence of a unit root in our sample is that it allows unbiased estimation using OLS.[4]

Table 5 shows that R&D innovators achieve a performance premium over non-innovators only during the three economically difficult periods 2001-2004, 2007-2010, and 2010-2012. They experience a 4-5 percentage points higher sales growth rate than non-innovators during these three periods. This observation is in line with H2, R&D innovators achieve a higher growth premium over non-innovators in times of economic downturns. There are no significant growth premiums visible for R&D innovators in the more prosperous economic environments 1996-1998, 1998-2001, 2004-2007, and 2012-2014. Consequently, we can partly accept H1 by saying that innovation activities of firms are positively related to firm growth. But it is key to note that the sales growth premium of R&D innovators is driven by the presence of the two economic downturns the Swiss economy experienced over the observed time span.

Table 6 also supports H2; growth differentials between R&D innovators and non-innovators are only visible in the three recessionary phases. For example, in the financial crisis of 2007-2010, small R&D innovators outgrew small non-innovative firms by more than 20 percentage points. A detailed look at Table 6 shows that the growth premium for R&D innovators is largest in 2007-2010, declines somewhat in 2010-2012, and finally vanishes in 2012-2014. This pattern nicely confirms our arguments; the renewal of the economy is complete after a certain time period (5 years in this case) because the economy has already adapted to the newly introduced products and processes by then; there are no more growth differentials between firms visible and a new cycle is about to start with new innovations entering the scene. In line with H3, Table 6 also shows that small R&D innovators outgrow large R&D innovators in the economic crisis of 2007-2010, the coefficients of $sales_{i,t-1}$ and of the interaction term are jointly significantly negative.

[4] If we consider whether there is indeed no convergence among firms, we should also look at some measure of variation over time (Egger and Pfaffermayr, 2009). Whereas the mean of the logarithmic turnover increased from 1996-2012, the standard deviation is remarkably stable around 1.8; that is, there seems to be no convergence within our sample.

In the two other recessionary phases, the two coefficients are jointly negative but not significant. However, they become significantly negative when we additionally introduce the lagged growth rate (see Table 7 under the next section Robustness Checks).

The significantly positive coefficient β_2 in Table 6 shows that the growth premium small R&D innovators enjoy over large R&D innovators is not just a matter of small scale, because in the three recessionary phases small R&D innovators outgrow small non-innovators, and this by more than they outgrow large R&D innovators. Actually, the small non-innovators seem to perform worst of all firms, as we also find significantly positive coefficients of $sales_{i,t-1}$ in Table 6 for the two recessionary periods 2001-2004 and 2010-2012. These two positive coefficients are not some sign of model instability but rather indicate a general advantage of large firm size in absence of innovation. A potential ad-hoc explanation for this positive correlation between size and growth in times of crisis for non-innovative firms is given by the findings of Nooteboom (1994) for services and Jovanovic (1994) and Klepper and Simons (2005) for manufacturing. These authors point out that not especially innovative, large firms are usually active in major markets where the industry life-cycle is well advanced and products are in a "cash cow" stage. These firms are, in sharp contrast to small non-innovative firms, less sensible to demand shocks because they produce well-established goods in a cheap way. The group of small non-innovative firms seems to be the most vulnerable to the competitive pressure taking place in times of recessions.

Table 5 and 6 both show that equity constraints are negatively related to sales growth rates in three out of the seven time periods, two of them recessionary. Hence, in economically adverse situations, firms with liquidity problems grow slower than their peers. This result reinforces the variable's credibility as a control for the lack of funds that may hinder small innovators from reorganizing their business during recessions. The variable measuring credit constraints is not significant in any of the observed time periods, emphasizing the importance of own and not of other funds in financing growth development. The coefficient of price competition shows a further interesting detail that confirms the notions of Schumpeter to some extent, namely that limited competition may be conducive to sales growth. Firms need to have a certain degree of appropriability to undertake investments that lead to higher sales growth. The negative and (partly) significant sign for the coefficient of price competition confirms this argumentation to some extent.

6 Robustness checks

Table 7 shows the same results as Table 6, but with the lagged growth rate as an additional control variable, which should correct for the presence of serial correlation (Coad and Rao, 2008). We see that serial correlation is generally not a problem, with the exception of the financial crisis of 2007-2010, where a coefficient of -0.149 shows substantial negative serial correlation. Negative serial correlation implies that an unobserved positive shock in a certain period reverts to an unobserved negative shock in the next period. This means that firms performing especially well in the preceding boom of 2004-2007 were also the ones suffering most during the subsequent recession. In our context, negative serial correlation implies that the coefficient of $sales_{i,t-1}$ is overestimated. However, Table 7 suggests that our results are quite robust also to the introduction of the lagged growth rate. The differences between small and large R&D innovators are significant on (at least) the 10% level in all three economic downturns. In light of the markedly reduced sample, induced by merging with an additional cross-section, this similarity of results also shows that sample selection due to non-response of firms may not be a too large issue.

A potential problem for our comparison of the performance of small and large firms is the fact that smaller firms have a higher probability of bankruptcy when facing a negative economic shock. Larger firms, in contrast, are more likely to only show negative growth rates but to still stay in business. In order to test for this potential problem, we run Equation (2) only for firms larger than a specific size threshold. A higher size threshold implies that the risk of bankruptcy due to size is more limited. Table 8 shows the results for an increase in the size thresholds from 5 to 30 employees. Again, results are very similar to the ones we obtained in Table 6 for the full sample. This robustness check also runs counter to the possibility that the better performance of the small, innovative firms is simply a spurious result caused by regression to the mean (Friedman, 1992). In their analysis of firm growth, Haltiwanger et al. (2013) identify regression to the mean effects and show that this is mainly an issue for firms with 5 and to a lesser extent for firms with 10 employees. Since our results do not prove to be sensitive to an increase of the minimum firm size up to 30 employees, we can conclude that regression to the mean should not be the driver behind the performance premium of small, innovative firms we observe.

Table 9 shows the results of the alternative dependent variable "situation after crisis". This is another way to identify the resilience of R&D innovators to the shock exerted by the financial crisis. The results are qualitatively similar compared to our growth regressions. R&D innovators have emerged stronger from the crisis. Even if they were hit harder by the crisis, they are in a better position at the end of the crisis.

Recall that we coded our central explanatory variable R&D innovation as product OR process innovation, based on R&D activities in the lagged period. However, the contribution of process innovations to our R&D innovation variable (i.e., firms do not at the same time also have a product innovation) is very minimal. Whereas our R&D

innovation variable has a mean of 0.339, a variable based on product innovations only has a mean of 0.312. We nonetheless kept our OR operationalization because R&D based process innovations are important for our story and would otherwise lower the coefficient of our R&D innovation variable. We wanted to have an empirical model as simple as possible and therefore also refrained from including more than one R&D innovation variable into our empirical model. However, running estimations for R&D based product innovations only shows that results are very similar to the ones we present in this paper. This implies that our results are to a large degree driven by product innovations. But it is crucial to see that product innovations go hand in hand with process innovations (70.5% in our case), and that process innovations always complement the introduction of a new product in the market.

There might be concerns that our results are driven by reverse causality, because we measure the contemporaneous correlation between R&D innovations and sales growth. Firms that grew fast in the lagged period might have more cash available in the current period, which may in turn accentuate the firm's innovativeness and would, in the case of serial correlation in the sales growth rate, lead to issues of reverse causality. We argue that this is not the case in our analysis. First, we have two control variables measuring the firm's liquidity situation regarding the financing of innovative activities in our model. Second, the robustness of our results in the presence of the lagged growth rate in Table 7 implies that past sales growth is not the driver behind the positive relation between R&D innovations and current sales growth. If past sales growth were, via the firm's innovativeness, the actual driver of our results, the lagged sales growth rate would capture this effect and the relation between innovation and current sales growth would vanish.

7 Conclusion

In this paper, we found, based on a representative panel data set of Swiss firms covering the period 1995-2014, an on average positive relation between firms' R&D innovations and their sales growth rates. However, we showed that this positive innovation-growth premium is rooted in the downturns of the macroeconomic business cycle. There are no visible difference between R&D innovators and non-innovators in the upturns of the macroeconomic business cycle. This means that in economic booms, where the surrounding business environment is relatively friendly, innovations do not put firms in an advantage over their less innovative competitors. When the economy expands, all firms can profit alike, irrespective of the novelty of the products they provide.

However, a booming economic environment also opens the door to substantial misallocations of resources, as both consumers and firms base their decisions on prices not adequately reflecting the fundamentals anymore. At some point this "irrational exuberance" peaks, and market participants start to notice their mistakes. They reduce spending and adapt their purchasing and investment decisions accordingly, meaning that they opt for less but better deals. Hence our result of a positive innovation-growth premium in recessions; by offering a higher utility or a lower price, innovative goods represent those better deals. It is in times of recessions where innovative firms gain market shares from their non-innovative competitors, setting in motion a process of renewal of the aggregate production structure of the economy. Our results show that this renewal of the economy is completed after about 3 years for mild recessions (2001-2004) and after about 5 years for more severe recessions (2007-2012). After that, the economy starts out a new cycle with firms introducing once again new products and processes. Consequently, we argue that looking only at aggregate growth rates of the economy hides the idea that business cycles play in inherent part in the replacement of the old with the new.

Finally, our results show that small innovative firms not only outgrow non-innovators but also achieve a better performance than large innovative firms. The various advantages of large R&D innovators in terms of their market dominance, economies of scale, and financial resources do not give them specific advantages over smaller innovators. To the contrary, organizational flexibility and a strong commitment to the firm make small R&D innovators able to timely adapt to changing circumstances, an ability that proves to be decisive in the discontinuous times of recession.

The results of this paper are important with respect to the impact of international business cycles on the economic situation of countries. Usually, when policy makers apply measures to foster the innovation activities of firms, the target is to increase nation well-being. However, our results suggest that as a secondary effect, such measures may also increase the resilience of firms against internationally triggered economic crises, because a country populated by firms producing innovative goods will be better protected from the pressure induced by a fall in demand on international markets. This may be one of the main reasons why Switzerland, which ranks among the top innovative economies in the world, navigated comparatively well through the last global financial crisis.

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Table 1: Sales growth rates for the 7 included time periods

Period:	Observations	Avg. Growth	Std. Dev.	Min	Max
1995-1998	802	0.063	0.3	-1.01	1.07
1998-2001	1053	0.093	0.26	-1.01	1.09
2001-2004	1119	-0.013	0.26	-1.07	1
2004-2007	1142	0.162	0.28	-1.06	1.09
2007-2010	1012	-0.016	0.26	-0.99	1.08
2010-2012	1190	0.008	0.22	-1.07	1.02
2012-2014	981	0.012	0.21	-1.02	1.07
Total	7297	0.043	0.27	-1.07	1.09

Table 2: Descriptive statistics of variables

Variable	Description	Obs	Mean	Std Dev	Min	Max
rnd_inno	Dummy variable, equals ”1” if there is an innovation in the current three year period and there has at the same time been R&D activity in the lagged three year period; ”0” otherwise	7297	0.34	0.47	0	1
sales	Logarithm of firm sales	7297	16.59	1.79	11	24.12
export	Share of exported goods or services (0-100)	7297	22.25	33.02	0	100
teduc	Share of employees having a tertiary degree (0-100)	7297	20.24	19.56	0	100
pcomp	Ordinal variable measuring perceived price competition, ranging from ”1” very weak to ”5” very strong	7297	3.93	1.04	1	5
equityc	Ordinal variable measuring equity constraints for financing of innovation projects, ranging from ”1” not relevant to ”4” very relevant	7297	2.2	1.11	1	4
creditc	Ordinal variable measuring credit constraints for financing of innovation projects, ranging from ”1” not relevant to ”4” very relevant	7297	1.94	1.06	1	4

Table 3: Estimations of Equation (1)

DV: $sales_{i,t}$ - $sales_{i,t-1}$	(1) OLS	(2) RE	(3) BE	(4) FE
rnd_inno	0.030***	0.031***	0.046***	0.007
	(0.008)	(0.008)	(0.011)	(0.012)
sales	0.002	-0.003	0.007***	-0.372***
	(0.002)	(0.003)	(0.003)	(0.012)
export	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
teduc	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
pcomp	-0.007**	-0.004	-0.011**	-0.002
	(0.003)	(0.003)	(0.005)	(0.004)
equityc	-0.014***	-0.010**	-0.026***	0.002
	(0.004)	(0.004)	(0.007)	(0.005)
creditc	0.003	0.001	0.013**	-0.008
	(0.004)	(0.005)	(0.007)	(0.005)
Constant	0.056**	0.089***	0.032	2.695***
	(0.028)	(0.034)	(0.038)	(0.303)
Observations	7,297	7,297	7,297	7,297
R-squared	0.077		0.074	0.317
Time fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Unit root test

DV: $sales_{i,t}$ - $sales_{i,t-1}$	(1) OLS	(2) GMM-SYS
$sales_{i,t-1}$	1.005***	1.014***
	(0.002)	(0.012)
Constant	-0.037	-0.179
	(0.036)	(0.205)
Observations	7,297	7,297
R-squared	0.980	
Time fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Region fixed effects	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: OLS estimation of Equation (2) on each cross section

DV: $sales_{i,t}$ - $sales_{i,t-1}$	(1) 2012-2014	(2) 2010-2012	(3) 2007-2010	(4) 2004-2007	(5) 2001-2004	(6) 1998-2001	(7) 1995-1998
rnd_inno	0.021	0.038**	0.048**	0.008	0.043**	0.022	0.009
	(0.018)	(0.017)	(0.023)	(0.023)	(0.019)	(0.021)	(0.027)
sales	0.001	0.002	-0.007	0.005	0.004	0.007	0.009
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)	(0.008)
export	-0.000	-0.000	-0.002***	0.001*	-0.000	-0.000	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
teduc	-0.001**	0.000	-0.001	0.001	-0.001*	0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
seduc	-0.001*	0.000	-0.000	0.001	-0.000	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
pcomp	-0.010	-0.014**	-0.008	-0.020**	-0.008	-0.008	0.001
	(0.007)	(0.006)	(0.009)	(0.008)	(0.007)	(0.008)	(0.011)
equityc	-0.001	-0.022**	-0.024	0.006	-0.026**	-0.031***	-0.007
	(0.011)	(0.010)	(0.015)	(0.011)	(0.011)	(0.011)	(0.015)
creditc	0.004	0.006	0.014	-0.013	0.000	0.014	0.003
	(0.011)	(0.010)	(0.016)	(0.012)	(0.011)	(0.012)	(0.014)
Constant	0.074	0.101*	0.176**	0.125	-0.111	0.098	0.046
	(0.055)	(0.056)	(0.072)	(0.132)	(0.117)	(0.090)	(0.075)
Observations	978	1,188	1,012	1,140	1,117	1,049	795
R-squared	0.057	0.077	0.158	0.114	0.107	0.088	0.129

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All regressions contain dummies for industries and regions

Table 6: OLS estimation of Equation (2) on each cross section

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV: $sales_{i,t}$ - $sales_{i,t-1}$	2012-2014	2010-2012	2007-2010	2004-2007	2001-2004	1998-2001	1995-1998
rnd_inno	0.074	0.203***	0.233***	0.028	0.148**	0.014	0.122
	(0.067)	(0.065)	(0.074)	(0.080)	(0.061)	(0.070)	(0.079)
sales	0.003	0.009*	0.002	0.006	0.010*	0.006	0.019**
	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.007)	(0.009)
rnd_inno*sales	-0.008	-0.026***	-0.030***	-0.003	-0.017*	0.001	-0.020
	(0.009)	(0.009)	(0.011)	(0.013)	(0.010)	(0.011)	(0.013)
export	-0.000	0.000	-0.002***	0.001*	-0.000	-0.000	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
teduc	-0.001**	0.000	-0.001	0.001	-0.001	0.001	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
seduc	-0.001**	0.000	-0.000	0.001	-0.001	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
pcomp	-0.011	-0.015**	-0.006	-0.020**	-0.005	-0.008	0.001
	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.008)	(0.011)
equityc	-0.001	-0.023**	-0.019	0.006	-0.027**	-0.031***	-0.006
	(0.011)	(0.010)	(0.014)	(0.011)	(0.011)	(0.011)	(0.015)
creditc	0.003	0.006	0.010	-0.013	0.002	0.014	0.002
	(0.011)	(0.010)	(0.014)	(0.012)	(0.011)	(0.012)	(0.014)
Constant	0.065	0.059	0.105	0.121	-0.166	0.101	-0.005
	(0.057)	(0.057)	(0.074)	(0.133)	(0.123)	(0.092)	(0.082)
Observations	978	1,188	1,010	1,140	1,114	1,049	795
R-squared	0.057	0.085	0.163	0.114	0.113	0.088	0.131

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

All regressions contain time branch and region fixed effects

Table 7: OLS estimation of Equation (2) on each cross section, including lagged growth rate

DV: $sales_{i,t}$ - $sales_{i,t-1}$	(1) 2012-2014	(2) 2010-2012	(3) 2007-2010	(4) 2004-2007	(5) 2001-2004	(6) 1998-2001
rnd_inno	0.050	0.209**	0.255***	0.059	0.203**	-0.003
	(0.079)	(0.103)	(0.090)	(0.117)	(0.079)	(0.090)
sales	0.005	0.001	0.015*	0.006	0.010	0.007
	(0.005)	(0.007)	(0.008)	(0.010)	(0.008)	(0.011)
rnd_inno*sales	-0.003	-0.029*	-0.032**	-0.010	-0.025**	0.006
	(0.011)	(0.016)	(0.013)	(0.018)	(0.012)	(0.015)
sales - sales = L,	-0.014	-0.025	-0.147***	-0.014	-0.039	0.003
	(0.047)	(0.018)	(0.037)	(0.083)	(0.050)	(0.043)
export	-0.000	-0.000	-0.002***	0.000	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
teduc	-0.001***	-0.000	-0.001	-0.001	-0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
seduc	-0.001***	0.000	-0.001	0.000	-0.001**	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
pcomp	-0.006	-0.016*	-0.005	-0.016	0.002	-0.012
	(0.009)	(0.009)	(0.011)	(0.012)	(0.010)	(0.014)
equityc	0.003	-0.015	-0.011	0.010	0.004	-0.043***
	(0.010)	(0.013)	(0.018)	(0.016)	(0.016)	(0.015)
creditc	-0.005	0.004	0.021	-0.028*	-0.038**	0.010
	(0.011)	(0.013)	(0.018)	(0.016)	(0.016)	(0.018)
Constant	-0.012	0.158	-0.038	0.024	0.316**	0.244*
	(0.065)	(0.118)	(0.162)	(0.095)	(0.124)	(0.130)
Observations	710	639	683	612	598	496
R-squared	0.085	0.120	0.191	0.122	0.129	0.174

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All regressions contain time branch and region fixed effects

Table 8: OLS estimation of Equation (2) on each cross section, firms with number of employees >30

DV: $sales_{i,t}$ - $sales_{i,t-1}$	(1) 2012-2014	(2) 2010-2012	(3) 2007-2010	(4) 2004-2007	(5) 2001-2004	(6) 1998-2001	(7) 1995-1998
rnd_inno	0.044	0.209***	0.209**	0.116	0.159	0.177*	0.090
	(0.080)	(0.072)	(0.098)	(0.127)	(0.114)	(0.097)	(0.132)
sales	-0.005	0.010	-0.001	-0.010	0.014	0.002	0.010
	(0.008)	(0.006)	(0.010)	(0.011)	(0.011)	(0.012)	(0.016)
rnd_inno*sales	-0.004	-0.026**	-0.026*	-0.011	-0.019	-0.022	-0.013
	(0.010)	(0.010)	(0.014)	(0.018)	(0.016)	(0.014)	(0.020)
export	0.000	-0.000	-0.002***	0.000	-0.000	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
teduc	-0.001*	0.000	-0.000	0.002**	-0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
seduc	-0.001	0.000	-0.000	0.002***	-0.001	-0.001**	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
pcomp	-0.014*	-0.010	-0.003	-0.024**	0.004	-0.019*	-0.019
	(0.008)	(0.007)	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)
equityc	0.007	-0.023**	-0.024	0.009	-0.041**	-0.031**	-0.011
	(0.014)	(0.012)	(0.015)	(0.015)	(0.016)	(0.014)	(0.020)
creditc	-0.010	0.005	0.005	-0.022	0.007	0.013	0.003
	(0.014)	(0.012)	(0.016)	(0.017)	(0.016)	(0.016)	(0.020)
Constant	0.164**	0.029	0.127	0.169	0.038	0.071	0.009
	(0.073)	(0.061)	(0.099)	(0.115)	(0.115)	(0.100)	(0.134)
Observations	712	866	695	711	663	665	490
R-squared	0.078	0.110	0.220	0.133	0.114	0.117	0.161

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All regressions contain time branch and region fixed effects

Table 9: Ordered logit estimation of variable "Situation after Crisis"

DV: Situation_after_crisis	(1) 2010-2012	(2) 2010-2012
rnd_inno	0.350**	1.069**
	(0.146)	(0.466)
sales	0.158***	0.190***
	(0.041)	(0.045)
rnd_inno*sales		-0.156*
		(0.095)
export	-0.003	-0.003
	(0.002)	(0.002)
teduc	0.000	0.000
	(0.003)	(0.003)
pcomp	-0.257***	-0.262***
	(0.058)	(0.059)
equityc	-0.103	-0.103
	(0.071)	(0.071)
creditc	0.030	0.027
	(0.065)	(0.065)
Constant cut1	-1.630***	-1.494***
	(0.451)	(0.455)
Constant cut2	-0.435	-0.297
	(0.450)	(0.453)
Observations	1,251	1,251

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All regressions contain time branch and region fixed effects